

# Concepts of Statistics and their implementation for data analysis

# Today's Outline

Part A : Statistics and its history  
Populations and samples  
Introduction of descriptive statistics

*Break – 5 min*

Part B : Frequencies and densities  
Data plots  
Introduction to probability and common distributions  
Hypothesis testing  
p-values

Class activity: Quiz –

# Today we will be learning:

- To identify and define statistics as a science
- To define populations and sample populations
- The meaning of descriptive statistics and their use in describing data
- The definition of frequencies and densities and their application in data analysis
- The definition of histograms and their use
- The concept of probabilities and definition of common distributions functions
- What are hypothesis testing and use of p-values

# What is Statistics?

Statistics is a science that studies the collection, the analysis, the interpretation, the presentation and organisation of data.

Based on mathematical tools, it allows to predict and forecast based on data that we observe (measure).

It is applicable to a wide variety of academic disciplines, from the natural and social sciences to the humanities, government and business.

Statistics deals with all aspects of data including the planning of data collection in terms of the design of surveys and experiments. This means that we need to consider all aspects of the design and this starts with establishing an appropriate experimental design.

*Adapted from Wikipedia*

# The History of statistics

**Statistics** started its history around 1749 although, however at that time it was restricted to information about states.

By the 19<sup>th</sup> century the interpretation of word statistics and its area of interest changed and later extended to include all collections of information of all types, to then be further extended to include the analysis and interpretation of such data.

Statistics increasingly used *probability theory*, whose initial results were found in the 17th and 18th centuries, particularly in the analysis of games of chance (gambling). Astronomy used probability models and statistical theories. *Statistical Inference* was then developed from this early probability theory and Statistics become the powerful science that is today.

In biology today it has a predominant role. Statistics is used for example for:

- Reproducibility of results
- Sound scientific methods
- Prediction of unknown

# The Faces of Statistics



Sir William Petty, a 17th-century economist who used early statistical methods to analyse demographic data.



Thomas Bayes  
1701-1761  
Develop the Bayes' Theorem foundation for Bayesian inference



Pierre-Simon, marquis de Laplace, one of the main early developers of Bayesian statistics. 1749- 1827



Carl Friedrich Gauss, mathematician who developed the method of least squares in 1809.  
(1777-1855)



Karl Pearson, the founder of mathematical statistics.  
1855-1936



Ronald Fisher, created the foundations for modern statistical science - 1890-1962

# Populations and Sample Populations

In statistics a *population* is the *total* set of observations that can be made of the group we are studying.

A population is any entire collection of people, animals, plants or things from which we observe data. It is the entire group under study that we wish to describe or draw conclusions about.

For example, if we are studying the height of adult women in UK, the population is ALL the women in UK. If we are looking at atomic behavior of a crystal, the population is every atom composing that crystal. If we are studying the average grade of students at Sheffield, the population is ....

In order to make any generalisations about a population, we often need to study a representative sample of that population.

A *sample population* is a set consisting of observations that are taken from the population. The methods with which we draw these observation is called sampling.

## Populations and Sample Populations (cont.)

The main difference between a population and sample there is to do with size, and how the observation are grouped:

A population includes **all** of the elements from a set of data.

A sample population consists of **one or more** observations from the population.

Sampling methods determine the *size* of the sample, that can have fewer observations than the population, the same number of observations, or more observations. More than one sample can be derived from the same population.

The population has quantifiable characteristics that are called *parameters* and denoted with Greek letters. Quantities like the mean or the standard deviations are parameters of the population.

Quantifiable characteristics of the sample population are called *statistics*. A sample statistic gives information about a corresponding population parameter. For example, the sample mean for a set of data would give information about the overall population mean ( $\bar{x}$ )



## Populations and Sample Populations (cont.)

A *sampling method* is a procedure for selecting sample elements from a population. Simple random sampling refers to a sampling method that has the following properties.

- The population consists of  $N$  objects.
- The sample consists of  $n$  objects.
- All possible samples of  $n$  objects are equally likely to occur.

It is what we generally do all to describe population because enables us to use statistical analysis. If sampling is not random we cannot use it.

When a population element can be selected more than one time, we are *sampling with replacement*. When a population element can be selected only one time, we are *sampling without replacement*.

There are many different ways of random sampling, they are based on distribution like Normal, uniform, binomial etc..

# Variables in statistics

**Variables are things that we measure**, control, or manipulate. They can be:

- Qualitative (names and lists) or Quantitative (counts and measurements).
- Continuous (can assume any value within a certain range) or discrete ( defined over separate values, qualitative or quantitative)

**Variables can be independent and not.** Independent variables are those that are manipulated, whereas dependent variables are only measured or registered as a consequence of a manipulation on another variable.

Most commonly we measure variables independently and then look for relations (**correlations**) between them.

In experimental research, we manipulate some variables and then measure the effects of this manipulation on other variables.

In the case we found that changing variable A we change variable B we then conclude that “A influences B “ and therefore we say that there is a causal relation between A and B.

# Descriptive statistics

Descriptive statistics is the term given to quantities that help to describe, show or summarise data in a meaningful way such that, for example, patterns might emerge from the data. They **DO NOT** enable to reach any conclusion on hypothesis that we might have made on the population.

They are important for: a) visualise the data; b) summarise the data

There are two general types of descriptive statistics:

***Measures of central tendency***: these are ways of describing the central position of a frequency distribution for a group of data. We can describe the central position using a number of statistics, including the mode, median, and mean.

***Measures of spread***: these are ways of summarizing a group of data by describing how spread out the data is. Measures of spread help us to summarize how spread out these scores are. We can describe the spread, using statistics including the range, quartiles, variance and standard deviation.

# Descriptive statistics (cont.)

Measure of central tendency also known as measure of central **LOCATION**.

mean

median

mode

Measure of spread, also known as measure of central **DISPERSION**.

range

variance

standard deviation

quartiles

# Mean, Median and Mode

**Mean:** it is the “average” value: the sum of observations divided by the number of observations. The mean of a sample is an un-biased estimator of the population mean.

We typically use  $n$  to represent the number of observations,  $x_i$  to represent the  $i$ th observation ( $x_1$  first observation,  $x_2$  second observation etc) and  $\bar{x}$  to represent the mean.

The sample mean is given by  $\bar{x} = (x_1 + x_2 + \dots + x_n) / n$

And it is often represented by  $\bar{x} = \sum_{i=1}^n x_i / n$  The population mean is the same  $\mu = \sum_{i=1}^N x_i / N$

**Median:** This is the value which divides the set of observations into two equal halves so that half the observations exceed the median and half are less than the median. Calculation of the median usually involves putting observations in RANK ORDER of size.

175 138 172 165 10 147 158

in rank order:

10 138 147 158 165 172 175

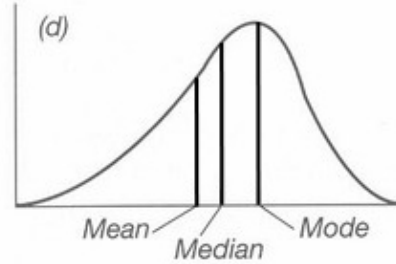
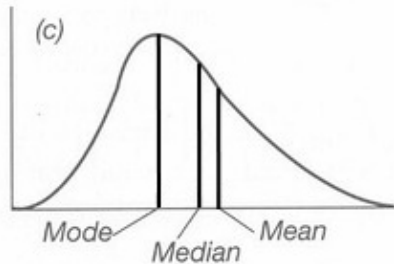
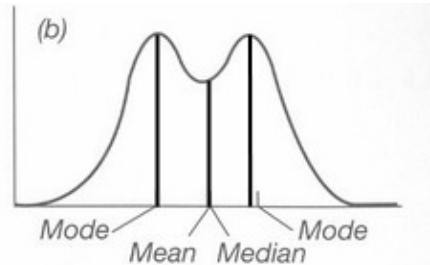
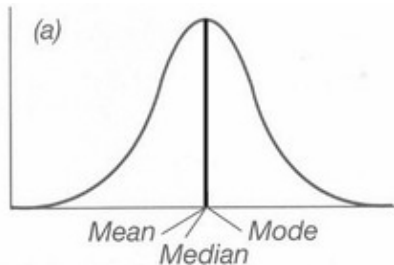
The median of this data is **158**.

The median has several advantages over the mean. For instance, for highly skewed distributions, extreme untypical values can have a strong influence on the mean. In this particular instance, what does the observation “10” do to the mean?

# Mean, Median and Mode (cont.)

**Mode:** The mode is the value which occurs most frequently: the most “fashionable” value. A sample population can have more than one mode. For continuous or qualitative measurements, the **MODAL CLASS** is the class with the highest frequency and it is not necessarily unique.

## examples



(a), (c) and (d) are unimodal  
(c) is positively skewed  
(d) is negatively skewed

Type of Variable	Best measure
nominal	Mode
ordinal	Median
Interval/Ratio (not skewed)	Mean
Interval/Ratio (skewed)	Median

# Range, Quartiles, Variance, and Standard Deviation

**Range:** This measures the **DIFFERENCE** between the largest and the smallest observation in the sample.

For example:

32.3 31.4 31.2 38.2 28.7 29.3 30.4 22.8 27.3 26.3

The largest observed value is 38.2 and the smallest is 22.8 hence the **range** is **38.2-22.8 = 15.4**

The range is really easy to calculate, but there are a number of drawbacks with this measure.

- It completely ignores the information provided by the remaining (n-2) observations and it is, by definition, strongly influenced by extreme untypical values.

**Quartiles:** are the three points that divide the data set into four equal groups, each group comprising a quarter of the data. The data is ranked before calculating the quartiles.

- The first quartile (Q1 or 25<sup>th</sup> percentile) is the middle number between the smallest number and the median of the data
- The second quartile (Q2 or 50<sup>th</sup> percentile) is the median of the data
- The third quartile (Q3 or the 75<sup>th</sup> percentile) is the middle value between the median and the highest value of the data
- IQR= interquartile range =  $Q_3 - Q_1$

## Range, Quartiles, Variance, and Standard Deviation (cont.)

**Variance:** This is one of the most important terms you will come across. This measures the average squared deviation of observations from their **population** mean.

In mathematical terms, let us assume we are dealing with an entire population, consisting of  $n$  observations with population mean  $\mu$ . Thus the variance of the population is

$$\sigma^2 = \sum_{i=1}^N (x_i - \mu)^2 / N$$

If all observations were exactly the population mean, then the average squared deviation of observations (hence variance) would be zero, but if they were more spread out then the variance would be higher. Why squared?



## Range, Quartiles, Variance, and Standard Deviation (cont.)

The variance within a population and the standard deviation within a population cannot be estimated directly from the variance and standard deviation calculated within a sample. The variance is NOT an un-biased estimator of the population.

It is clear when we compare the range of a population with the range from a sample. Why?

The sample range will tend to underestimate population range. In the same way, the variance and standard deviation in a sample would tend to underestimate that of a population. To correct this, we use slightly altered formula to get un-biased estimators.

Variance of sample population

$$\text{var} = \sum_{i=1}^N (x_i - \bar{x})^2 / (N - 1)$$

Standard deviation of the sample population

$$sd = \sqrt{\sum_{i=1}^N (x_i - \bar{x})^2 / (N - 1)}$$

The **standard deviation** of an entire population is the square root of the variance of that population

## Part B

# Today's Outline

Part A : Statistics and its history  
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Introduction of descriptive statistics

*Break – 5 min (questions if any)*


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Data plots  
Introduction to probability and common distributions  
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Class activity: Quiz – part A and B

# Frequency distributions

A *frequency distribution* is a table that displays the occurrence of various outcomes in a sample, each counted within a particular group or interval.

If you have a pool of 100 students and ask them to answer to the following question: *The use of statistics in biology is a great advantage*  
You gather the following data

Strongly agree	20	 Frequency or count
Agree somewhat	30	
Not sure	20	
Disagree somewhat	15	
Strongly disagree	15	

***Univariate frequency distribution***

## Frequency distributions (cont.)

You can also create ranges of values to group the data. For example if you are summarising the same pool of 100 students by their weight, you can gather the data in the following form:

	# of students	Cumulative #
bins	Less then 50kg	25
	50–55 kg	60
	55–60 kg	80
	60–65 kg	100

Cumulative distribution

Some of the graphs that can be used with frequency distributions are histograms, line charts, bar charts and pie charts. Frequency distributions are used for both qualitative and quantitative data.

## Frequency distributions (cont.)

There are frequency table that describe more than one variable and they are called *joint frequency distribution* (two-ways contingency table)

In the dataset "Popular Kids," students in forms 4-6 were asked whether good grades, athletic ability, or popularity was most important to them. A two-way table separating the students by forms and by choice of most important factor is shown below:

	Form			
Choice	4	5	6	Total
-----				
Grades	49	50	69	168
Popular	24	36	38	98
Sports	19	22	28	69
-----				
Total	92	108	135	335

**Q: What would be a quick way to describe possible differences among the students' choices by form?**  
**Later in the quiz....**

# Probability density function

A *probability density function* (PDF)  $f_x$ , or density of a continuous random variable  $x$ , is a function that describes the relative likelihood for this random variable to take on a given value. The probability density function is non-negative everywhere, and its integral over the entire space is equal to one.

$$P(a \leq x \leq b) = \int_a^b f_x(x) dx \quad \text{or} \quad P(X) = \int f_x(x) dx$$

The **sample space**  $X$  for a probability model is the set of all possible outcomes. An *random variable representing an event*  $x$  is a subset of the sample space  $X$ .

A **probability** is a numerical value assigned to a given event  $x$ . The probability of an event is written  $P(x)$ , and describes the long-run relative frequency of the event. The first two basic rules of probability are the following:

**Rule 1:** Any probability  $P(x)$  is a number between 0 and 1 ( $0 \leq P(x) \leq 1$ ).

**Rule 2:** The probability of the sample space  $X$  is equal to 1 ( $P(X) = 1$ ).

# Common probability distribution functions

We will look at the details of three probability distribution functions.

These are commonly used in data analysis and we will make extensive use of them in our module.

- Uniform distribution
- Binomial distribution
- Normal distribution (Gaussian probability distribution)



# Uniform Distribution

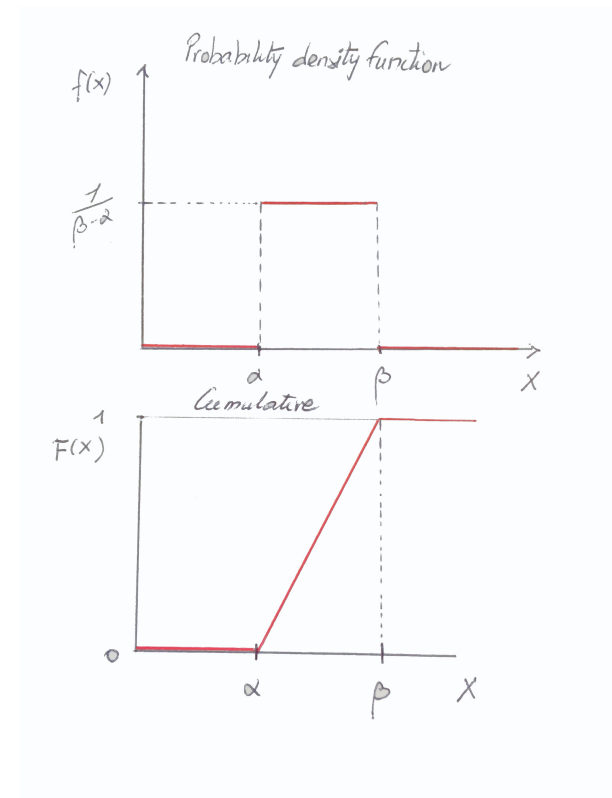
Uniform distribution (also known as rectangular distribution) is a family of symmetric probability distributions that can be continuous or discrete

*Continuous uniform distribution* ( $U(\alpha, \beta)$ ) is such that all intervals of the same length on the distribution's space are equally probable. The space is defined by the two parameters,  $\alpha$  and  $\beta$ , which are its minimum and maximum values of the distribution.

$$f(x) = \begin{cases} \frac{1}{\beta - \alpha} & \text{for } \alpha \leq x \leq \beta \\ 0 & \text{for } x < \alpha \text{ and } x > \beta \end{cases}$$

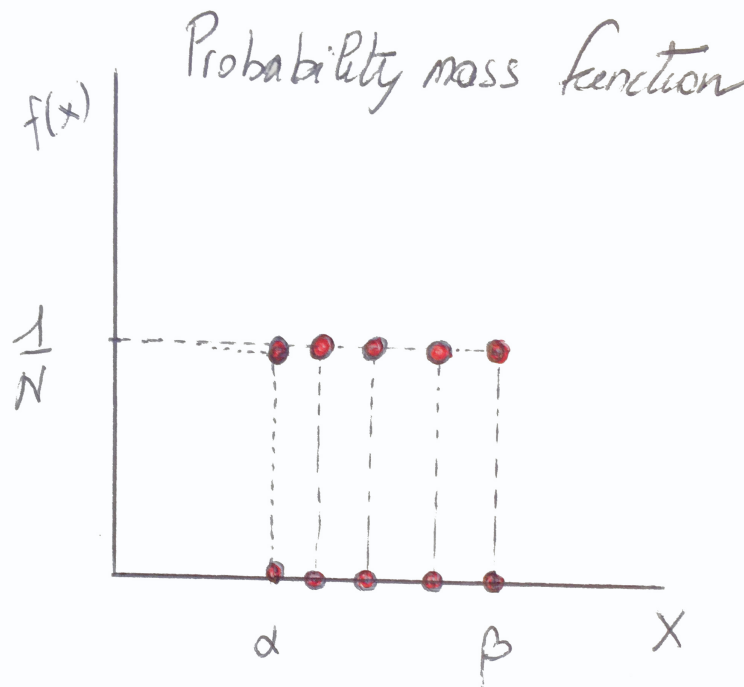
Later in the quiz... mean, median and mode?

Variance:  $\sigma^2 = \frac{1}{12}(\beta - \alpha)^2$



## Uniform Distribution (cont.)

It is when a finite number of values ( $N$ ) are equally likely to be observed. Every values has equal probability  $1/N$  to occur.



$$F(x) = 1/N$$

Mean ?

Median ?

Mode ?

variance 
$$\frac{(\beta - \alpha + 1)^2 - 1}{12}$$

# Binomial Distribution

The *binomial distribution* with parameters  $n$  and  $p$  is the discrete probability distribution of the number of successes in a sequence of  $n$  independent success/failure experiments, each of which has a probability of success equals to  $p$ .

The binomial distribution is the basis for the popular binomial test of statistical significance.

The binomial distribution is frequently used to model the number of successes in a sample of size  $n$  drawn with replacement from a population of size  $N$ .

If the sampling is carried out without replacement, the draws are not independent and so the resulting distribution is a hypergeometric distribution, not a binomial one. However, for  $N$  much larger than  $n$ , the binomial distribution is a good approximation, and widely used.

## Binomial Distribution (cont.)

Example: What is the probability of getting 3 heads from 10 throws of a coin?

Let there be  $n$  trials in which each trial results in one of two outcomes (e.g. success / failure).

Let the probability of one of the outcomes arising in a given trial (arbitrarily called "success") be  $p$  (therefore failure occurs with probability  $q$ , where  $q = 1 - p$ )

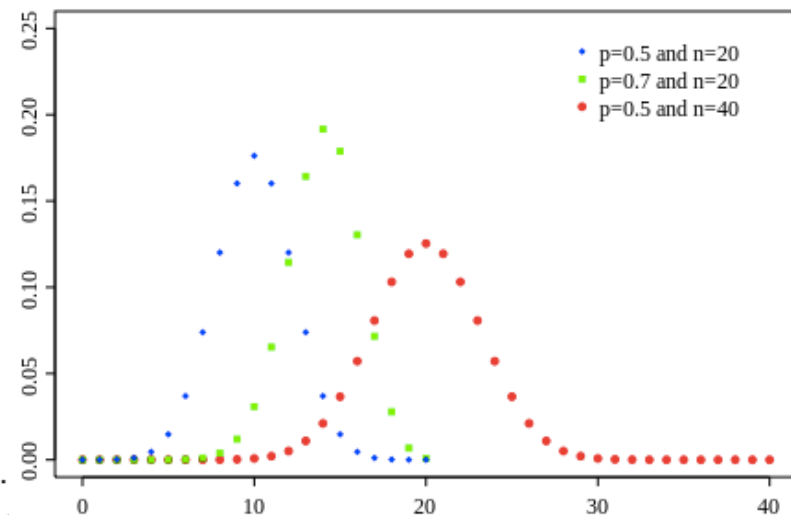
In general, if the random variable  $X$  follows the binomial distribution with parameters  $n$  and  $p$ , we write  $X \sim B(n, p)$ . The probability of getting exactly  $x$  successes in  $n$  trials is given by the *probability mass function*:

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$$

$$\binom{n}{x} = \frac{n!}{x!(n-x)!}$$

Mean  $np$   
Median not unique  
Variance  $np(1-p) = npq$

$$\text{mode} = \begin{cases} \lfloor (n+1)p \rfloor & \text{if } (n+1)p \text{ is 0 or} \\ (n+1)p \text{ and } (n+1)p - 1 & \text{if } (n+1)p \in \{1, \dots, n\} \\ n & \text{if } (n+1)p = n+1. \end{cases}$$



# Normal Distribution

The **normal distribution**, also called the **Gaussian distribution**, is an important family of continuous probability distributions, applicable in many fields. Each member of the family may be defined by two parameters, *location* and *scale*: the mean ( $\mu$ ) and variance ( $\sigma^2$ ) respectively. The **standard normal distribution** is the normal distribution with a mean of zero and a variance of one.

The importance of the normal distribution as a model of quantitative phenomena is due in part to the central limit theorem. Many measurements, ranging from psychological to physical phenomena (in particular, thermal noise) can be approximated, to varying degrees, by the normal distribution.

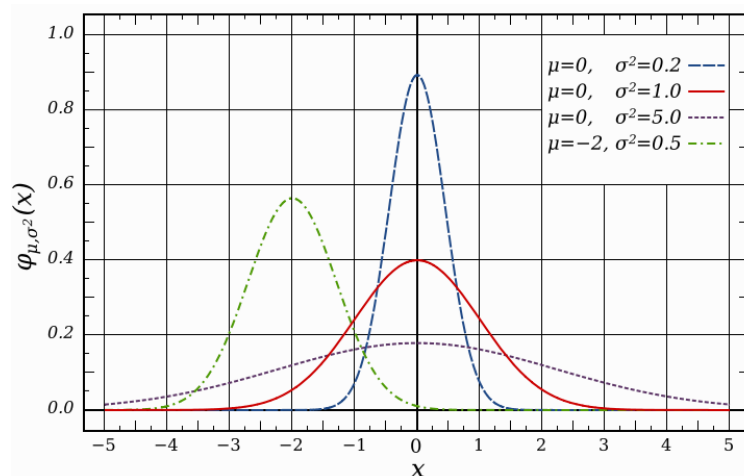
The normal distribution also arises in many areas of statistics. For example, the sampling distribution of the **sample mean** is approximately normal, even if the distribution of the population from which the sample is taken is not normal.

Probability density function:

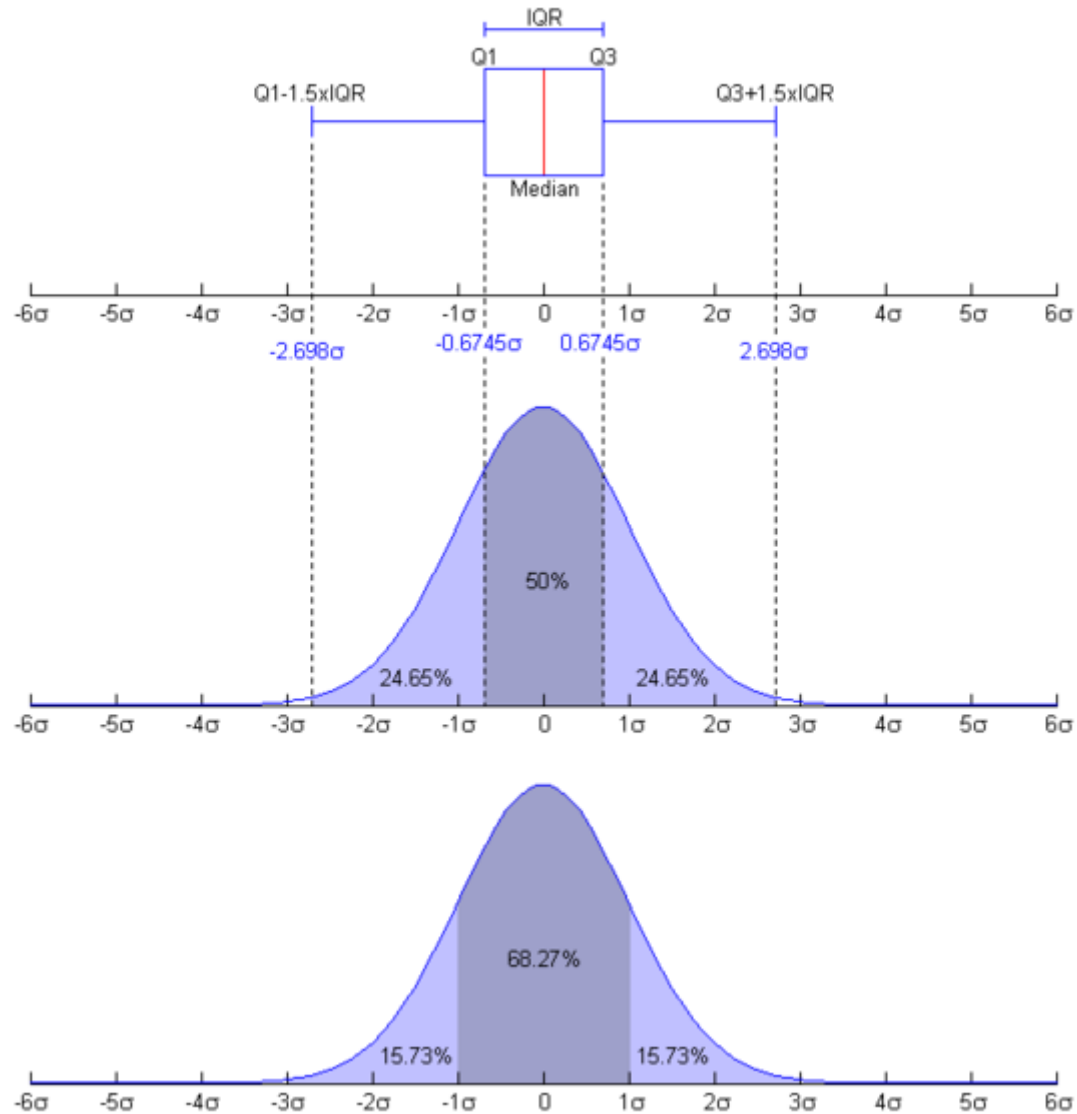
$$\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Mean = Median = Mode =  $\mu$

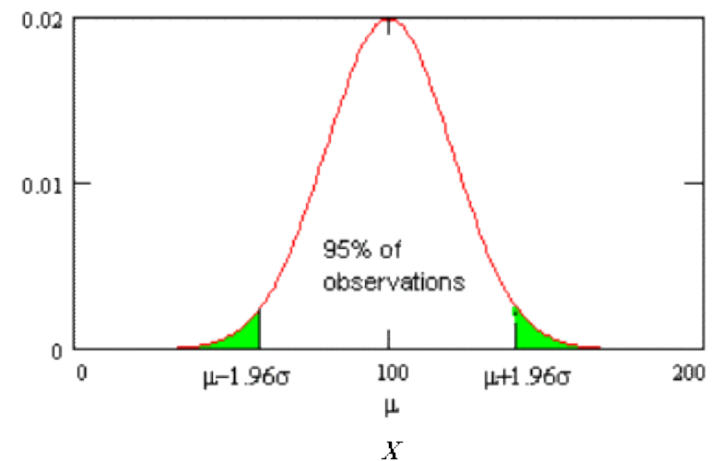
Variance =  $\sigma^2$



# Normal Distribution



One important property is that the **mean  $\pm$  1.96** standard deviations contain 95% of all observations while the **mean  $\pm$  2.576** standard deviations contain 99% of observations.

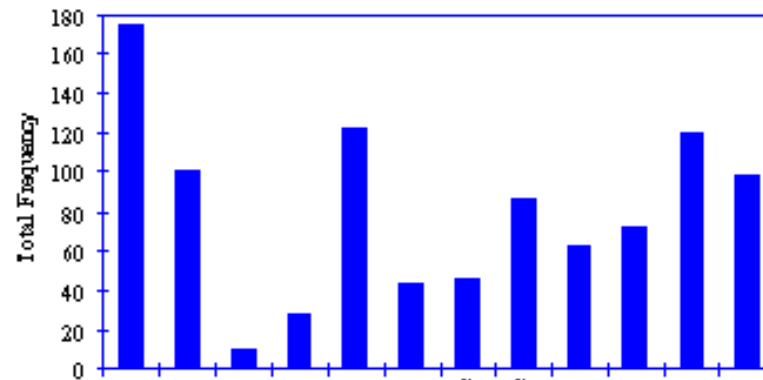


# Data Visualisation: Bar Charts

Discrete data:

**A way of summarising discrete (qualitative or quantitative) data is by counting the number of observations falling into each category.**

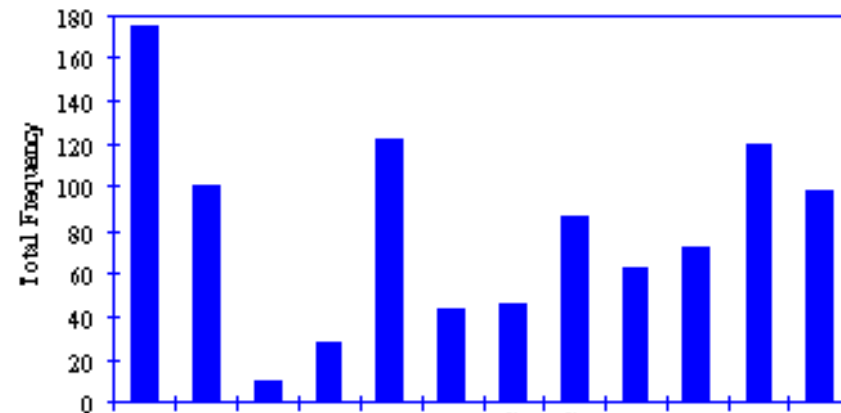
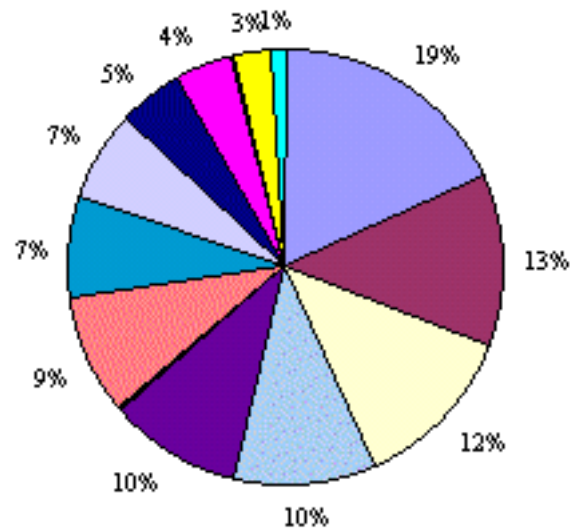
The *relative frequency* is a number which describes the proportion of observations falling in a given category. We can plot the total frequency in a chart called **bar chart**



# Data Visualisation: Pie Chart

The graphical representation of relative frequencies or percentages is a **Pie chart**.

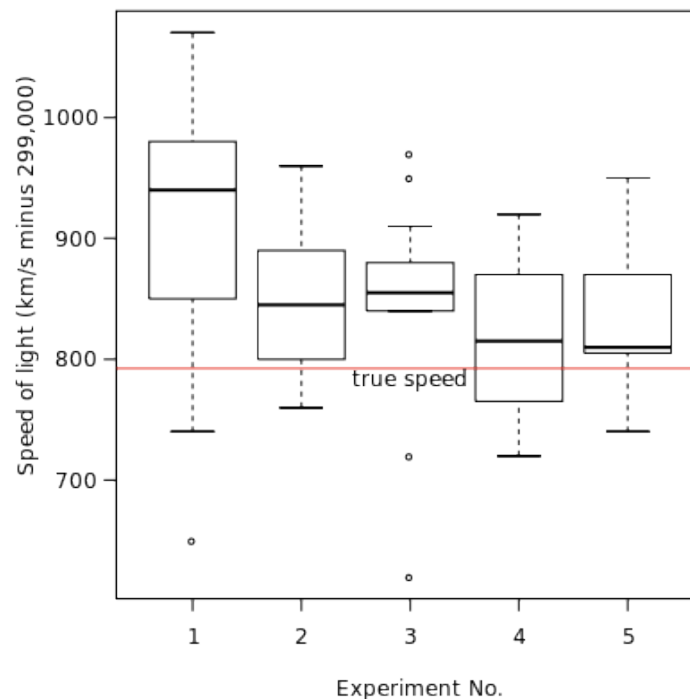
It is more appropriate, when we need to highlight proportions rather than counts. Each slice of the pie represents a proportion of the total.





## Data visualisation: box plot

A **box plot** is a graphical representation of groups of numerical data through their quartiles. Box plots may also have lines extending vertically from the boxes (whiskers) indicating variability outside the upper and lower quartiles, hence the terms box-and-whisker plot and box-and-whisker diagram. Outliers may be plotted as individual points.



Box plot of data from the Michelson–Morley experiment, 1887

# Data visualisation: Histogram

It is an estimate of the *probability distribution* of a continuous variable (quantitative variable) and was first introduced by Karl Pearson

To estimate this **distribution** we can proceed in the same way as the bar chart but we first **grouping the observations**. This consists in choosing a set of contiguous non-overlapping intervals, called class intervals (or bins), the observations can be grouped to form a discrete variable from the continuous variable.

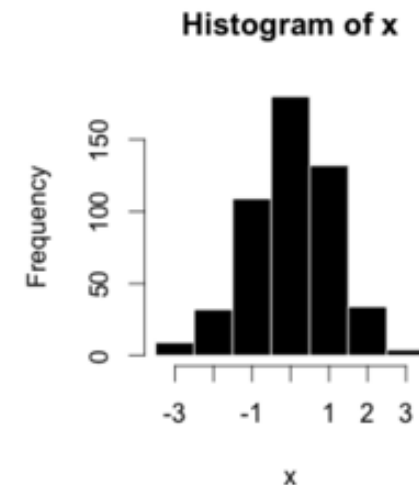
1. Identify suitable, non-overlapping classes in which to put this data. Generally, between 5 and 15 classes is best.

Calculate the range and divide it by the chosen number of intervals to get the approximate length for each interval.

Define interval end points so they don't overlap or leave gaps (ie. they are mutually exclusive and exhaustive) - This ensures that every observation belongs in exactly one interval.

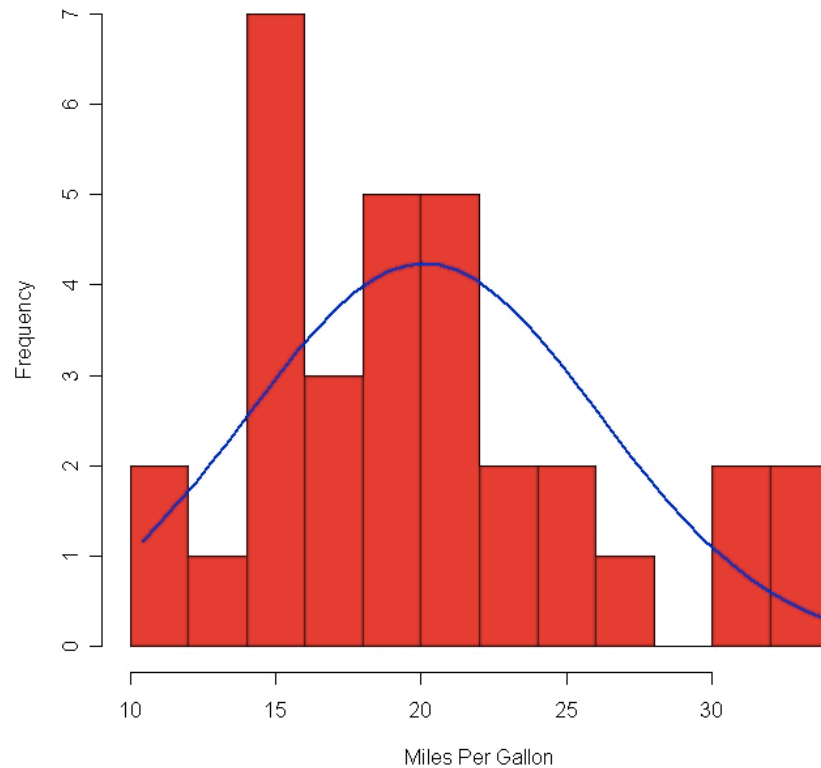
2. Count the number of observations that fall in the classes.

Histograms give a rough sense of the *density* of the underlying distribution of the data and often are used as density estimators ( to estimate *the probability density function* of the underlying variable)

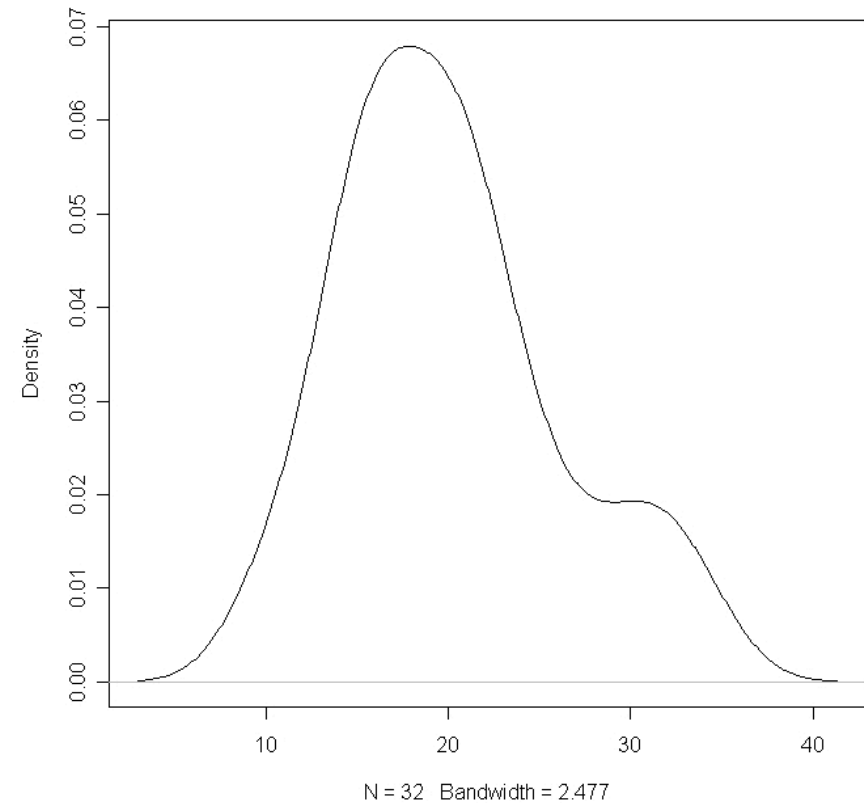


# Probability density function (cont.)

Histogram with Normal Curve



density.default(x = mtcars\$mpg)



Why is the histogram not estimating well the density function?

# Statistical tests

The ultimate goal of most statistical tests is to evaluate relations between variables, in general to evaluate a ratio of some measure of the differentiation common in the variables in question to the overall differentiation of those variables.

*When is this relationship significant?*

The significance depends mostly on the **sample size**.

In very large samples, even very small relations between variables will be significant.

In very small samples even very large relations cannot be considered reliable (significant).

*How do we quantify significance?*

Thus, in order to determine the level of statistical significance, we need a function that represents the relationship between "magnitude" and "significance" of relations between two variables, depending on the sample size.

This function would give us the significance level (p-value), and it would tell us the probability of error involved in rejecting the idea that the relation in question does not exist in the population (null hypothesis).

However, in most cases we know its shape and can use it to determine the significance levels for our findings in samples of a particular size and also can be related to the normal function.

# Confidence and p-values

**The statistical significance of a result is the probability that the observed relationship (e.g., between variables) or a difference (e.g., between means) in a sample occurred by pure chance, and that in the population from which the sample was drawn, no such relationship or differences exist.**

In other words, statistical significance of a result tells us something about the degree to which the result is "true" (in the sense of being "representative of the population").

The measure that we normally use to quantify this is a **p-value**.

p-value represents a decreasing index of the reliability of a result. The higher the p-value, the less we can believe that the observed relation between variables in the sample is a reliable indicator of the relation between the respective variables in the population. Specifically, the **p-value represents the probability of error that is involved in accepting our observed result as valid**, that is, as "representative of the population."

For example, a p-value of .05 (i.e.,  $1/20$ ) indicates that there is a 5% probability that the relation between the variables found in our sample occurs by chance. Thus assuming that in the population there was no relation between those variables whatsoever (independent events), we could expect that approximately in every 20 replications of the experiment there would be one in which the relation between the variables in question would be equal or stronger than in ours.

# Structure of a test

- Research question  
Your investigative question  
Ex: Do people have a preference for movie type?
- Hypotheses  
The null hypothesis ( $H_0$ ), which is the hypothesis that states there is no significant difference between expected and observed data. Investigators either accept or reject  $H_0$ .  
 **$H_0$ :** The observed distribution fits the expected or, in other words, there is no preference.  
 **$H_A$ :** The observed distribution does not fit that expected (there is a preference).
- Assumptions  
The sample is chosen randomly.  
The scores are independent (i.e., each subject is allowed only one preference).  
The null hypothesis.
- Decision Rule  
This is the threshold by which  $H_0$  is excepted or rejected – p-value threshold
- Computation  
The calculation of the appropriate descriptive statistics
- Decision

# Type of tests

In the literal meaning of the terms, a **parametric statistical test** is one that makes assumptions about the parameters (defining properties) of the population distribution(s) from which the data are drawn. A **non-parametric test** is one that makes no such assumptions.

Nonparametric tests are also called distribution-free tests because they don't assume that the data follow a specific distribution.

When your data don't meet the assumptions of the parametric test, especially the assumption about being normally distributed, it is the case to use non-parametric tests. It is a basic rule , but there are additional considerations.

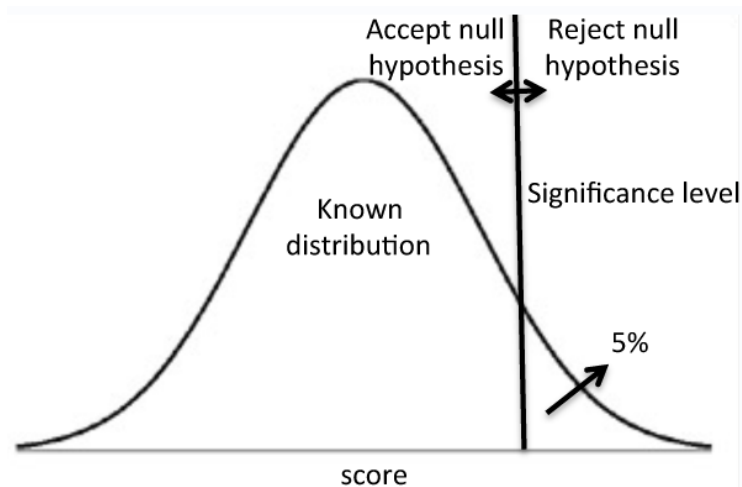
Examples:

- Parametric analysis to test group means.
- Nonparametric analysis to test group medians

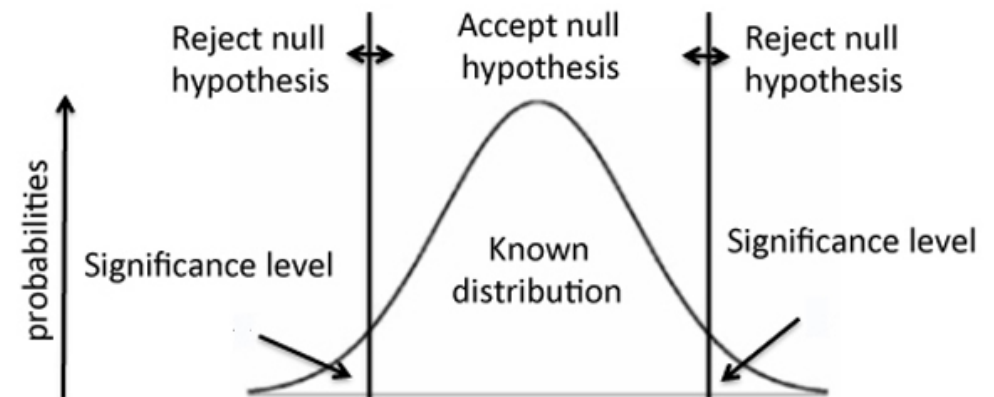
<http://blog.minitab.com/blog/adventures-in-statistics/choosing-between-a-nonparametric-test-and-a-parametric-test>

# One-tailed and two-tailed test

One-tailed test



Two-tailed test



Significance level = p-value =  $\tau = 0.05$

$t = (\bar{x} - \mu) / (s / \sqrt{n})$       t score used in at test to compute the decision

- Known population normally distributed
- The sample is randomly selected
- The s of the unknown population is the same as the known population



# Summary

- How to define populations and sample populations in your study
- Descriptive statistics and their use in data analysis
- Frequency and densities and their application in data analysis
- Probabilities and definition of common distributions functions
- Basic data representation tools and definition of histograms and their use
- What are hypothesis testing and use of p-values